IN THE UNITED STATES PATENT AND TRADEMARK OFFICE	
Declaration under 37 CFR 1.132	Atty. Docket No. **BERR1100-1**

Applicants **Keith L. Berrier**	
Application Number **10/799,560**	Date Filed **03/11/2004**
Title **Systems and methods for reconstructing information using a Duncan and Horn formulation of the Kalman filter for regularization**	
Group Art Unit **3709**	Examiner **Patton, Amanda K.**
Confirmation Number: **7773**	

Commissioner for Patents
P.O. Box 1450
Alexandria, VA 22313-1450

Dear Sir:

My name is Michael E. Lisano, II.

I have a doctorate in Aerospace Engineering, and am a specialist in applied estimation theory and filtering. I have written linearized, extended, and sigma-point forms of Kalman filters over the past 12 years in the U.S. space program, and I have discovered basic mathematical principles related to consider covariance filtering.

I would state that it is not intrinsically obvious, without performing an investigation of the filter applied to a system of interest, that using a particular sort of recursive state-parameterized estimator (such as a Kalman filter) to solve any particular noise-rejection/signal-recovery problem (e.g., the inverse problem of electrocardiography) will necessarily work.

As discussed in the literature, Kalman filters exist of many different formulations (the linearized Kalman filter, the extended Kalman filter, the sigma-point Kalman filter, and others). These filters are all limited by the basic assumptions of the method of calculating the Kalman gain, which makes a linear relation between the correction to the estimated state or signal, and

the observed error between the measured and predicted signals (said error including not only the noise we seek to reject, but also the effects of our own mismodeling).

When faced with a highly nonlinear and noisy signal such as an electrocardiographical signal, and moreover in the absence of a precisely-derivable a-priori model or "plant" for the time-varying behavior, one is left with attempting to apply the various filter formulations, and "tuning" the filter to accommodate the inadequacies of the a-priori model. Only then can one determine whether one has successfully rejected noise (and only noise), and recovered the sought-after noise-free signal to any successful extent (e.g. to some required level to make the application work in some broader system, such as a medical application, or in my own work, a filter working in tandem with a spacecraft's control system).

In conclusion, unless a program of deliberate research is followed, a researcher – even an expert with considerable experience in applying Kalman filters to a wide range of problems – will not know with immediate certainty (i.e., it will not be "obvious") whether any particular Kalman filter formulation (Duncan & Horn, sigma-point, extended, iterated, linearized, etc.) would be effective in recovering a noise-free signal from some nonlinear, stochastic system (such as measurements of heartbeats). In other words, based on algorithm descriptions in the literature, the specialized features of a particular nonlinear filtering formulation might offer apparently-attractive abilities for solving such a problem, but these features may be found to have hard-and-fast limitations in the presence of the particular problem. This is not something that is definite and knowable a-priori – such limitations, or the lack thereof, can only be determined by experimentally implementing such a filter and subjecting it to tests.

Michael E. Lisano, II, Ph.D.

Date: Oct. 1, 2007